Pervasive Detection of Sleep Apnea using Medical Wireless Sensor Networks

Osman Salem[1], Yaning Liu[2] and Ahmed Mehaoua[1]
[1]LIPADE Laboratory, University of Paris Descartes, France
[2]JCP-Consult, Rennes, France
{osman.salem, ahmed.mehaoua}@parisdescartes.fr
yaning.liu@jcp-consult.com

***Abstract*—The sleep apnea is a sleep disorder characterized by cessation of respiratory flow (apnea) or a reduction in the flow (hypopnea). This disorder is often invalidating and may in some cases lead to death. During the night, symptoms can include nocturnal choking, heavy snoring, sweating, restless sleep, impotence, and witnessed apnea. As the sleep centers for apnea detection are usually overloaded and inaccessible, an automatic apnea detection algorithm for portable devices is required for in-home detection. In this paper, we propose a lightweight approach for pervasive detection of sleep apnea using Wireless Sensor Networks. The experimental results show that our proposed approach achieves good detection accuracy with low delay and low false alarm rate.**

***Index Terms*—Obstructive Sleep Apnea, Heart Rate Variability, Anomaly Detection, Wireless Sensors Networks**

I. Introduction

The Sleep Apnea (SA) is a sleep disorder characterized by cessation of respiratory flow (Apnea) or a reduction in the flow (Hypopnea) during the night. This disorder is invalidating and may in some cases lead to death. During the night, those affected by sleep apnea are awakened often every 30 seconds or occasionally once every few nights. It causes hypoxia, fragmented sleep, daytime fatigue, headache, hypertension, diabetes, obesity, cardiovascular disease, myocardial infarction, stroke, sudden cardiac death, etc.

Symptoms of apnea include nocturnal choking, asphyxia, high blood pressure, heavy snoring, sweating, headache, restless sleep and fainting. The sleep apnea is a common and often misunderstood disease. The danger it poses to patients on cardiopulmonary plane, neuro-psychiatric, social and professional repercussions (e.g., difficulty in concentrating, slower reaction, impotence, irritability, etc.) still unknown and underestimated. Sleep apnea disturbs normal sleep which is essential to maintain mental and physical health.

The sleep apnea can be observed at any age. Men under 60 years are primarily affected. Their incidence in the general population is not well known, and it is currently estimated in the range of 0.3 to 4%. However, it still under-diagnosed where less than 20% of affected persons are aware and diagnosed with apnea.

Apnea must be recognized and treated in time to prevent serious cardiovascular health complications that lead to death when apnea is not properly detected and treated. This syndrome affects the quality of life not only of those who are affected, but also those around them.

Sleep apnea is classified into three different types: Obstructive Sleep Apnea (OSA), Central Sleep Apnea (CSA) and Mixed Sleep Apnea (MSA). In OSA, the airway is blocked (at least for 10 seconds) due to the collapse of upper airway, while respiratory effort against obstruction of the upper airway continues. In CSA, the respiratory effort is absent (or reduced) due to lack of neural input from the nervous system, but the airway is open in this type of apnea. In MSA, both types (OSA and CSA) are present. OSA is the most frequent type, especially with patients suffering from obesity. CSA type is rarely alone and usually it appears with other types.

More than 80% of apneic patient are not aware of the problem [1] and the diagnosis is requested based on doctor's suspicions. To find out if the patient has sleep apnea, the analysis of a complete record of sleep called polysomnography (PSG) is needed, where the patient has to spend the whole night in a sleep monitoring center. This involves recording several physiological parameters [2] such as an electroencephalogram (EEG) to measure electrical activity of the brain, electrocardiogram (ECG) to measure electrical activity of the heart, Electromyogram (EMG), nasal airflow, abdominal effort, thoracic effort, oxygenation ratio (SpO2), snoring, etc. The PSG test is expensive, inconvenient, uncomfortable and time consuming for both patients and evaluators. In fact, the identification of apnea and its type is performed manually by sleep experts through the analysis of recorded data.

The Apnea-Hypopnea Index (AHI) is obtained by counting the number of apnea and hypopnea over the whole night and calculating the average on a per-hour basis. AHI is generally used to classify the apnea into several levels: $AHI \leq 5$ for normal level, $[5-15]$ for mild level, $[15-30]$ for moderate and $AHI \geq 30$ for severe [2], [3]. However, PSG is expensive and time consuming. Furthermore, the sleep centers are usually overloaded. The waiting time for a test is more than 6-months. This may cause health complications, cardiovascular damages or even death.

The dependency on PSG needs to be replaced by simpler, automated and faster detection technique. Therefore, the development of pervasive techniques to conduct the sleep apnea test in-home may reduce the healthcare cost and the waiting

978-1-4799-6644-8/14/$31.00 ©2014 IEEE

time for an appointment and for test result. It will also allow the sleep laboratory to focus on patients with severe apnea or other antecedent health complications.

Sleep apnea is a respiratory problem, but its effect can be observed from many peripheral systems (ECG [4], [5], SpO2 [6], [7], thoracic signals, etc.). The ECG provides a valuable information about apnea through the analysis of RR interval (beat-by-beat) as shown in figure 1. Cardiac activity is characterized by a regular rhythm with a constant RR space. The RR interval is commonly named Heart Rate Variability (HRV). The P, Q, R, S and T waves in figure 1 are produced by arterial depolarization and ventricular repolarization.

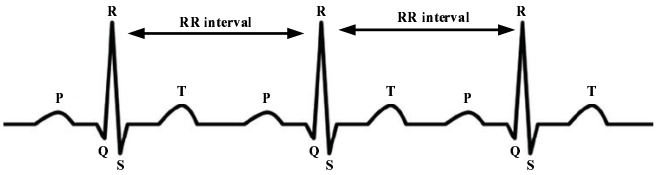

Fig. 1. RR interval on an ECG trace

We consider a general deployment scenario, where a set of 3 electrodes are disposed on the patient's body as shown in figure 2. Each of these electrodes returns an ECG signal from different views of the heart. These electrodes are connected to a transceiver (wireless mote) which in turn transfers the measurements to the Local Processing Unit (LPU) which is usually a SmartPhone or tablet device, for real time processing and OSA detection.

Wireless Body Area Networks (WBANs) are an important monitoring tool for the prediction and the early detection of sleep apnea. The early detection is essential for the treatment. It is important to note that the acquisition of ECG signal using single electrode or other light biometric technologies has been investigated and widely available in the market.

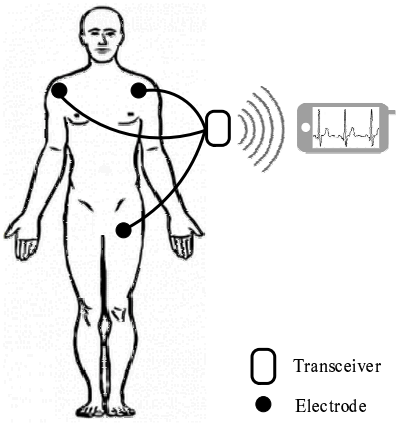

Fig. 2. WSN used to measure ECG signal

In this paper, we propose a lightweight approach to identify sleep apnea using WBANs. We aim to develop a simple, reliable and real-time apnea detection system which is able to automatically adapt to the user physiological parameters in order to detect change. We begin by collecting the ECG signal on LPU and we proceed by filtering the ECG signal to remove noise and prepare the signal for further analysis. Afterward, we extract the position of R peaks in one minute time slot, and we derive the RR intervals ($RR_i = R_i - R_{i-1}$). The derived RR interval time series is filtered and outliers are removed using median sliding window.

The proposed approach is based on the residual time series analysis of successive RR-intervals. We use the root mean square of successive RR intervals and the Z-test to detect change in hypothesis. If the null hypothesis is rejected, the minute is classified as apneic, otherwise, the minute is classified as normal.

The rest of this paper is organized as follows. Section II briefly reviews most relevant related work for sleep apnea detection. Section III presents our proposed approach for sleep apnea detection. In section IV, we present our experimental results using real apnea-ecg database. Section V concludes this paper.

II. Related work

Several approaches have been proposed and analyzed for the detection of sleep apnea and they are based on different techniques, such as machine learning classification [3], [5], [8]–[10] and autoregressive model [11]. Many physiological parameters have been used in apnea detection, such as ECG, respiration rate, SpO2, thorax and abdomen effort signal, etc. to increase the detection accuracy. Authors in [8] propose a novel approach for classifying sleep apnea using cross wavelet transform by considering the airflow and thoracic effort as input signals and principal component analysis for dimensionality reduction.

The effectiveness of using the minimally-invasive finger sensor (SpO2) for the automated detection of apnea in infants has been investigated and analyzed in [7]. Photoplethysmographic has been used in [12] to detect OSA in children through the simple use of pulse oximeter (SpO2) and the analysis of Pulse Rate Variability (PRV). Their approach is simple, economical and comfortable but the detection accuracy still lower than other approaches based on HRV.

The apnea affects respiration activities and cardiovascular system. Usually, heart rate decreases during apnea and increases during restoration of breathing. With the development of mobile heath and wearable sensors, significant efforts have been made based on ECG analysis and on the extraction of beat morphology features which are known as ECG Derivative Respiration (EDR) [4], [11], [13].

In [14], a cost-effective approach has been proposed to detect OSA without using ECG signal. The proposed approach derives respiration data (or EDR) from ECG signal using Empirical Mode Decomposition (EMD), and extract features from EDR and HRV using Recurrence Quantification Analysis (RQA). Various data mining and machine learning methods have been applied on extracted features for classification [10], [15], [16]. Common methods include Decision Tree (DT), K-Nearest Neighbor (KNN), Artificial Neural Networks (ANN),

Naïve Bayes (NB), AdaBoost and Support Vector Machine (SVM). SVM is the most recommended classification method as it provides the higher precision with low computational complexity [5], [10], [17]. A real-time sleep apnea detection using single-lead ECG is proposed in [4]. It consists of an external ECG sensor, a microcontroller, an Android computing platform and a server that identifies OSA episodes. However, classification approaches generally require resources not available for in-network processing.

Authors in [18] compare the performance of three ECG derived respiratory signals (R wave area, RR-interval and R peak amplitude) in OSA detection. They found that R wave area has better performance than HRV for OSA detection, and R peak achieves the worst performance. In [19], authors compare four EDR methods based on R amplitude, RS amplitude, QRS area and ECG filtering in the respiratory frequency band ($[0.2 - 0.4]$ Hz). The results show that R amplitude generates the best approximation of the respiratory signal.

Many studies analyze the detection accuracy of apnea using the HRV features from nocturnal ECG [9], [20] and classification algorithms (SVM, KNN, NN, etc.). In this paper, we propose a real time approach for early detection of apnea on the LPU. The proposed approach is based on three major steps: data preprocessing, feature extraction and time series analysis.

III. Proposed Approach

We consider a general deployment scenario where ECG signal is acquired by non-invasive wireless sensor and transmitted to a smart phone or Local Processing Unit (LPU) for real time processing as shown in figure 2. The received ECG data are used to detect the position of R peaks after the preprocessing and filtering of the received ECG signal. The exact determination of the location of R wave is essential to derive RR interval time series. The R detection is achieved by two successive differentiation, averaging and squaring techniques, as referred in [21].

The occurrence times of R peaks are used to extract RR interval time series as the difference between two consecutive R peaks. We apply a sliding window of 1 minute on the resulted RR intervals as shown in figure 3, and we analyze the RR interval minute by minute in non overlapping manner to detect sleep apnea and to derive the number of apneic minutes per hour of sleep (AHI). The block diagram of our proposed approach is shown in figure 4. ECG signal preprocessing is an

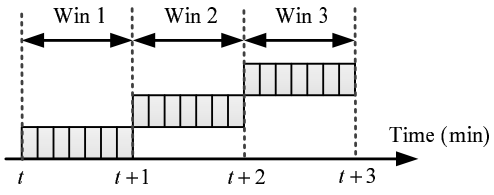

Fig. 3. Sliding Window

important step to discard electrode contact noise, interference, baseline drift and motion artifacts. As the signal has a useful

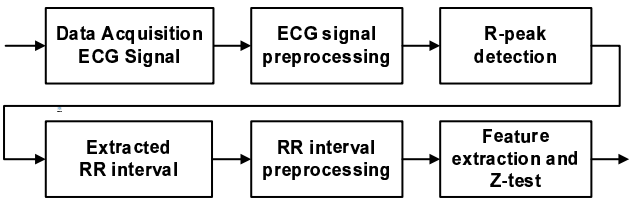

Fig. 4. Block representation of various analysis procedures

frequency in the interval $[0.5 - 40]$ Hz, filtering techniques have been used to remove noise.

To detect apnea, we use the HRV to analyze the variation of time interval between consecutive R peaks (or heart beats). This time interval is denoted by RR-interval. Due to ectopic beats or miss detection of R peaks, errors are inevitable and introduce faulty values in R-peak time. Therefore, a preprocessing step is required to remove outliers from RR-interval time series.

Let $RR = [RR_i, RR_{i+1}, \ldots, RR_{i+m}]$ denotes the set of RR intervals during the last m minutes. To filter data from outliers, we use the median of the normal last ten RR_i intervals to replace detected outliers by median. The median is computed by excluding values outside the interval $[0.4 - 2]$ in second. RR values falling inside the previous interval are used to calculate the median. The current RR value which satisfies the condition in equation 1 (within 20% of the median) is kept in the filtered time series. Outliers are substituted by the median of the filtered data in the sliding window.

$$0.8 \times medRR \leq RR_i \leq 1.2 \times medRR \quad (1)$$

The resulted Normal-to-Normal NN-interval time series was further resampled with the frequency 1 Hz using cubic-spline interpolation, detrended and smoothed. After the correction of RR intervals, the features from time and frequency domains are extracted and analyzed to detect sleep apnea. Temporal features [5], [20] include: AVNN (the mean of NN intervals), SDNN (the standard deviation of NN intervals), RMSSD (Residual Mean Square of Successive Difference of NN intervals), SDSD (Standard Deviation of the Successive Difference), NNx (defined as the number of successive NN intervals $|NN_{i+1} - NN_i| > x$ ms), pNN50, pNN20 and pNN10 (defined as the percentage of NNx over the total number of RR interval in 1-minute length), SDANN (the standard deviation of 5-minutes NN interval means), correlation coefficients, Alan factors, etc. In frequency domain, applied features include Power Spectral Density (PSD), Very Low Frequency (VLF) $[0.003 - 0.04]$ Hz, Low Frequency (LF) $[0.04 - 0.15]$ Hz, High Frequency (HF) $[0.15 - 0.5Hz]$, LF/HF (ratio of low to high frequency), etc.

The use of temporal features is more adequate for in-network processing, as they require less computation complexity than frequency domain. To provide a lightweight approach with first diagnosis, we test whole temporal features, and we found that RMSSD and SDANN are able to capture wide range of variability. There, for real time processing, we focus only

on the RMSSD time series associated with root mean square of the mean of the squared difference between successive NN intervals (in ms):

$$RMSSD_j = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}\left(RR_i - RR_{i-1}\right)^2} \quad (2)$$

To classify each minute as either Apnea or Normal minute, we use the z-test to determine if the current value of $RMSSD_j$ follows the same distribution as previously classified normal values. In Z-test, the null hypothesis H_0 (normal hypothesis or N class) is rejected if the z-scores is greater than a predefined threshold th. The z-scores is calculated as:

$$Z = \frac{RMSSD_j - \mu_0}{\sigma_0} \quad (3)$$

Where μ_0 and σ_0 are the mean and the standard deviation in the hypothesis H_0 of $RMSSD_j$. A threshold of z-scores of $th = 1.96$ is associated with a p-value of 0.025 and a confidence level of 95% of the measurements, and a threshold of $th = 2.56$ is associated with a p-value of 0.005 and a confidence level of 99.73%. However, a large value of threshold could result in miss detection of low NN variations, and thus leading to low detection accuracy and reduced AHI value. Therefore, we set the threshold for z-scores to $th = 1.96$.

The μ_0 and σ_0 are calculated using the Exponentially Weighted Moving Average (EWMA):

$$\mu_0 = \alpha\mu_0 + (1-\alpha)RMSSD_j \quad (4)$$

$$\sigma_0 = \alpha\sigma_0 + (1-\alpha)\left(\sqrt{\left(RMSSD_j - \mu_0\right)^2}\right) \quad (5)$$

Where α is the smoothing parameter lower than 1 ($\alpha \in [0,1]$). We use a value of $\alpha = 0.7$ to make the estimation less sensitive to fluctuations and more dependant on past values. Furthermore, we exclude the apneic values of $RMSSD_j$ which exceed the $1.25 \times \mu_0$ from poisoning the estimation of the mean and the standard deviation. The pseudo code of the proposed algorithm is given in algorithm 1.

Algorithm 1 Detection algorithm

```
Preprocess the received ECG signal
R peak detection
RR_i = R_i − R_{i−1}
Segment the RR intervals into 1 minute
Preprocess the RR intervals
Compute the RMSSD_j
Z = (RMSSD_j − μ_0)/σ_0
if |Z| ≥ 1.96 then
    Label the minute as apneic
end if
if (RMSSD_j < 1.25 × μ_0) then
    μ_0 = αμ_0 + (1 − α)RMSSD_j
    σ_0^2 = ασ_0^2 + (1 − α)(RMSSD_j − μ_0)^2
end if
```

IV. Experimental results

To conduct experiments and evaluate the performance of our proposed approach, we use real patient datasets from apnea-ecg database from physionet [22]. There is 70 ECG records, and each contains approximately 8 hours of single lead ECG. The signal was sampled at 100Hz. The available records in apnea-ecg are annotated for 30 men and 5 woman (35 records) between 27 and 63 years and their weight ranges from 53 to 135 kg.

Each minute was labeled with A (Apnea) or N (Normal). Other 35 records are not annotated per minute, but an additional file containing AI (Apnea Index), HI (Hypopnea Index) and AHI (Apena-Hyponea Index) is provided, where $AHI = AI + HI$. The annotations were provided by sleep experts on the basis of many physiological parameters (SpO2, respiration, airflow, ECG, etc.). The record name starts with: C for normal class ($AHI < 5$), B for borderline or moderate apnea ($5 \leq AHI < 15$) and A for apnea patients ($AHI \geq 5$). Each record is divided into 1-min segments and each minute is annotated with A or N by sleep experts. These 3 data classes allow designers and developers to test the accuracy of their proposed approaches.

Figure 5 shows the raw ecg signal for the used patient (record a02) from apnea-ecg database. We can clearly notice inside this figure the presence of abnormal variations and outliers. However, the individual heartbeats are not visible at this time scale. Figure 6 focus on few heartbeats, where we can notice the different waves (P, Q, R, S, T). We apply the R peak detection algorithm to extract the position (time instant) of R. The result of this detection procedure is displayed in figure 7 with dashed vertical line.

The occurrence times of R peaks are extracted from the previous step, and the RR interval can easily be derived as the difference between 2 successive R peak instants. The resulted RR time series (in sec) is displayed in figure 8. The RR interval contains outliers associated with ectopic and miss detected R peaks. The filtered RR intervals (or NN intervals) using median sliding window is displayed in figure 9. The detrending and smoothing results over NN intervals are displayed in figure 10.

After the preprocessing step of RR intervals, the feature extraction procedure is used to derive ECG measurements from the NN-intervals. The variation of the mean of RR during 1-min time slot is shown in figure 11, where the mean fluctuates around zero. In the same manner, the variation of the standard deviation is shown in figure 12. The variation of RMSSD feature is shown in figure 13, where it exhibits a similar variation of the variance. The Z-test is applied on the RMSSD to classify minutes into normal or apneic using a value of $Z = 1.96$.

We also extract other features, such as the pNN20 and pNN50 defined as the percentage of NN intervals $p_{NN} > 20\%$ and $p_{NN} > 50\%$ respectively. The results of pNN20 and pNN50 are displayed in the figure 14. These features (pNN20 and pNN50) are calculated as the percentage of the number

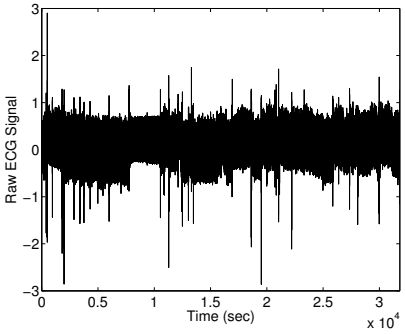

Fig. 5. Raw ECG signal

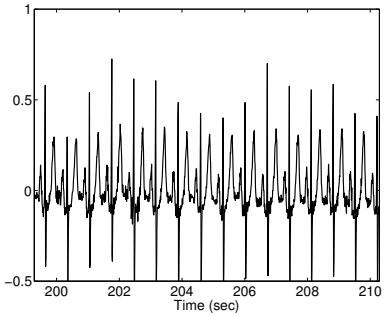

Fig. 6. Zoom over 15 heartbeats

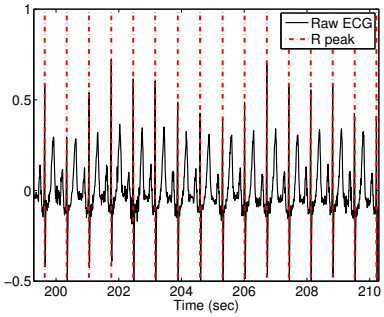

Fig. 7. Raw ECG and R peaks detection

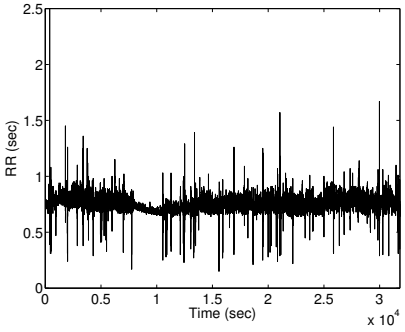

Fig. 8. RR intervals

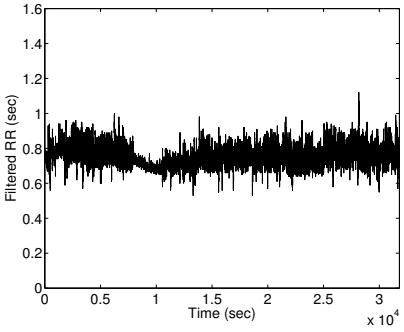

Fig. 9. Filtered NN intervals

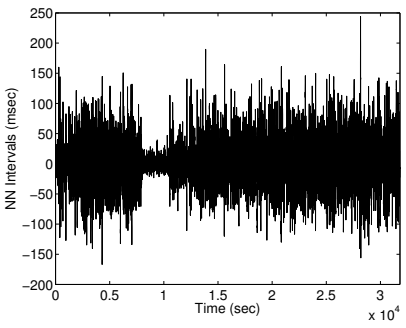

Fig. 10. NN after detrending and smoothing

of intervals Δ ($|\Delta = NN_i - NN_{i-1}|$) that exceed 50ms (for pNN50) or 20ms (for pNN20) over the total number of δ in the processed window (1 minute). The number of NN-interval exceeding the specified range is called NN50 or NN20. We then compute the number of NN50 or NN20 over the total number of NN intervals in a sample of one minute. If this ratio exceeds 50% for pNN50 (or 20% for pNN20) we conclude that the analyzed minute is apneic.

It is important to note the poor performance achieved by pNN50 in figure 14, where only a few minutes are apneic (at most 9 minutes). However, the AHI index for this record from annotation file $AHI = 69.5$. In the other side, pNN20 can achieve a good detection accuracy if the appropriate value of threshold is used. Figure 15 shows the SDANN features over 5-minutes that can be exploited to detect sleep apnea. However, as this feature is calculated over 5-minutes and our objectify is to provide online detection, we use the RMSSD in our approach.

To evaluate the performance of the proposed approach, we analyze the impact of the z-scores threshold th on the detection accuracy. The binary decision for each minute is compared to the expert annotations. The False Positive Ratio (FPR) given in equation 7 and the True Positive Ratio (TPR) given in equation 6 are evaluated. The different choices of th in z-scores produce the Receiver Operating Characteristics (ROC). Figure 16 shows the ROC for the proposed approach where the detection probability reaches 100% for a FAR of 18%.

$$TPR = \frac{TP}{TP + FN} \times 100\% \quad (6)$$

Where TP is the number of true positives, and FN is the number of false negatives. FPR is defined as the ratio of incorrectly detected apneic minutes:

$$FPR = \frac{FP}{FP + TN} \times 100\% \quad (7)$$

Where FP is the number of false positives and TN is the number of true negatives. The verification process of TP, FP, TN and FN was performed using the classification information provided in the annotation file.

V. Conclusion

In this paper, we present a lightweight approach for early and pervasive detection of sleep apnea using wireless sensor networks. The proposed approach is based on the analysis of RR intervals derived from the ECG signal to distinguish between normal and apneic minutes. The building block of the proposed approach and experimental result are presented. Our experimental results show that our proposed approach achieves good detection accuracy as a primary evaluation test for further analysis in sleep lab. The most important contribution of this work is a lightweight approach easy to implement and interpret.

References

[1] A. Nassir and O. Barnea, "Wireless body-area network for detection of sleep disorders," in *IEEE 27th Convention of Electrical Electronics Engineers in Israel (IEEEI'12)*, 2012, pp. 1–5.

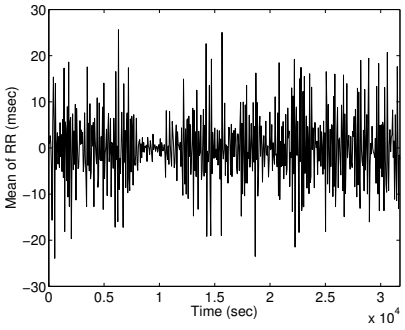

Fig. 11. Mean of NN intervals

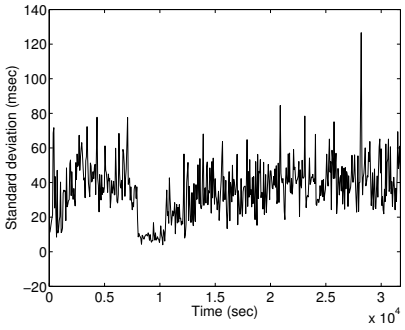

Fig. 12. Standard deviation of NN intervals

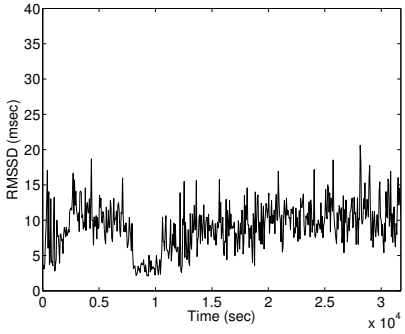

Fig. 13. RMSSD

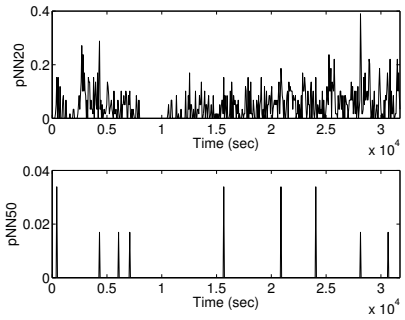

Fig. 14. pNN20 and pNN50

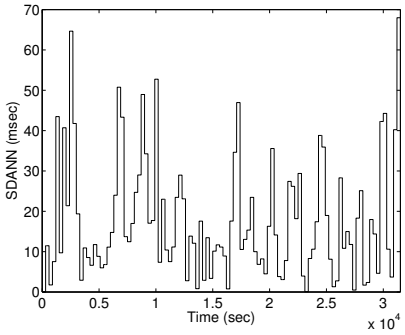

Fig. 15. SDANN

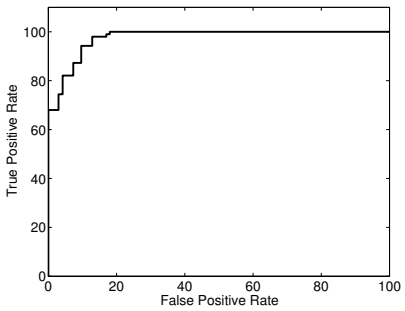

Fig. 16. ROC

[2] American Academy of Sleep Medicine Task Force, "Sleep-Related Breathing Disorders in Adults: Recommendations for Syndrome Definition and Measurement Techniques in Clinical Research," *Sleep*, vol. 22, no. 5, pp. 667–689, 1999.

[3] B. Koley and D. Dey, "Classification of Sleep Apnea using Cross Wavelet Transform," in *1st Int. Conf. on Condition Assessment Techniques in Electrical Systems (CATCON'13)*, 2013, pp. 275–280.

[4] M. Bsoul, H. Minn, and L. Tamil, "Apnea MedAssist: Real-time Sleep Apnea Monitor Using Single-Lead ECG," *IEEE Trans. on Information Technology in Biomedicine*, vol. 15, no. 3, pp. 416–427, 2011.

[5] L. Almazaydeh, K. Elleithy, and M. Faezipour, "Detection of obstructive sleep apnea through ecg signal features," in *IEEE International Conference on Electro/Information Technology - EIT*, 2012, pp. 1–6.

[6] L. Almazaydeh, M. Faezipour, and K. Elleithy, "A Neural Network System for Detection of Obstructive Sleep Apnea Through SpO2 Signal Features," *International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 3, no. 5, 2012.

[7] G. Cohen and P. de Chazal, "Automated detection of sleep apnea in infants using minimally invasive sensors," in *35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC'13)*, 2013, pp. 1652–1655.

[8] M. E. Tagluk, M. Akin, and N. Sezgin, "ClassifiCation of Sleep Apnea by Using Wavelet Transform and Artificial Neural Networks," *Expert Syst. Appl.*, vol. 37, no. 2, pp. 1600–1607, 2010.

[9] M. Al-Abed, K. Behbehani, J. Burk, E. Lucas, and M. Manry, "A New Method to Detect Obstructive Sleep Apnea Using Fuzzy Classification of Time-Frequency Plots of the Heart Rate Variability," in *28th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS'06)*, 2006, pp. 6493–6496.

[10] B. Koley and D. Dey, "Adaptive classification system for real-time detection of apnea and hypopnea events," in *IEEE Point-of-Care Healthcare Technologies (PHT'13)*, 2013, pp. 42–45.

[11] M. O. Mendez, A. M. Bianchi, M. Matteucci, S. Cerutti, and T. Penzel, "Sleep Apnea Screening by Autoregressive Models From a Single ECG Lead," *IEEE Transactions on Biomedical Engineering*, vol. 56, no. 12, pp. 2838–2850, 2009.

[12] J. Lázaro, E. Gil, J. M. Vergara, and P. Laguna, "Pulse Rate Variability Analysis for Discrimination of Sleep-Apnea-Related Decreases in the Amplitude Fluctuations of Pulse Photoplethysmographic Signal in Children," *IEEE Journal of Biomedical and Health Informatics*, vol. 18, no. 1, pp. 240–246, 2014.

[13] A. H. Khandoker, J. Gubbi, and M. Palaniswami, "Automated Scoring of Obstructive Sleep Apnea and Hypopnea Events Using Short-Term Electrocardiogram Recordings," *IEEE Transactions on Information Technology in Biomedicine*, vol. 13, no. 6, pp. 1057–1067, 2009.

[14] K. Karandikar, T. Q. Le, A. Sa-ngasoongsong, W. Wongdhamma, and S. T. Bukkapatnam, "Detection of Sleep Apnea Events via tracking Nonlinear Dynamic Cardio-Respiratory Coupling from Electrocardiogram Signals," in *6th Annual International IEEE EMBS Conference on Neural Engineering*, 2013, pp. 1358–1361.

[15] J. Gubbi, A. Khandoker, and M. Palaniswami, "Classification of Obstructive and Central Sleep Apnea Using Wavelet Packet Analysis of ECG Signals," in *Computers in Cardiology*, 2009, pp. 733–736.

[16] T.-P. Kao, J.-S. Wang, C.-W. Lin, Y.-T. Yang, and F.-C. Juang, "Using Bootstrap AdaBoost with KNN for ECG-based Automated Obstructive Sleep Apnea Detection," in *The 2012 International Joint Conference on Neural Networks (IJCNN'12)*, 2012, pp. 1–5.

[17] H. Al-Angari and A. V. Sahakian, "Automated Recognition of Obstructive Sleep Apnea Syndrome Using Support Vector Machine Classifier," *IEEE Transactions on Information Technology in Biomedicine*, vol. 16, no. 3, pp. 463–468, May 2012.

[18] L. S. Correa, E. Laciar, V. Mut, A. Torres, and R. Jané, "Sleep Apnea Detection based on Spectral Analysis of Three ECG - Derived Respiratory Signals," in *31st Annual International Conference of the IEEE EMBS*, 2009, pp. 4723–4726.

[19] D. Widjaja, J. Taelman, S. Vandeput, M. A. Braeken, R. A. Otte, B. R. V. den Bergh, and S. V. Huffel, "ECG-derived respiration: Comparison and new measures for respiratory variability," in *Computing in Cardiology*, 2010, pp. 149–152.

[20] K. Ramya and K. Rajkumar, "Respiration Rate Diagnosis Using Single Lead ECG in Real," *Global J. of Medical research*, vol. 13, no. 1, 2013.

[21] J. Pan and W. J. Tompkins, "A Real-Time QRS Detection Algorithm," *IEEE Transactions on Biomedical Engineering*, vol. BME-32, no. 3, pp. 230–236, 1985.

[22] "Physionet," http://www.physionet.org/physiobank/database/mimicdb, Last visited 2014.